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Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system

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ABSTRACT

The first objective of this study is to determine the theoretical potential of solar irradiation in Indonesia by using artificial neural networks (ANNs) method. The second objective is to visualize the solar irradiation by province as solar map for the entire of Indonesia. The geographical and meteorological data of 25 locations that were obtained from NASA database are used for training the neural networks and the data from 5 locations were used for testing the estimated values. The testing data were not used in the training of the network in order to give an indication of the performance of the system at unknown locations. In this study, the multi layer perceptron ANNs model, with 9 inputs variables i.e. average temperature, average relative humidity, average sunshine duration, average wind speed, average precipitation, longitude, latitude, latitude, and month of the year were proposed to estimate the monthly solar irradiation as the output. Statistical error analysis in terms of mean absolute percentage error (MAPE) was conducted for testing data to evaluate the performance of ANN model. The best result of MAPE was found to be 3.4% when 9 neurons were set up in the hidden layer. As developing country and wide islands area, Indonesia has the limitation on the number of meteorological station to record the solar irradiation availability; this study shows the ANN method can be an alternative option to estimate solar irradiation data. Monthly solar mapping by province for the entire of Indonesia are developed in GIS environment by putting the location and solar irradiation value in polygon format. Solar irradiation map can provide useful information about the profile of solar energy resource as the input for the solar energy system implementation.

Contents

1. Introduction

The Republic of Indonesia is an archipelago stretching along the equator including a vast number of islands. It is located between

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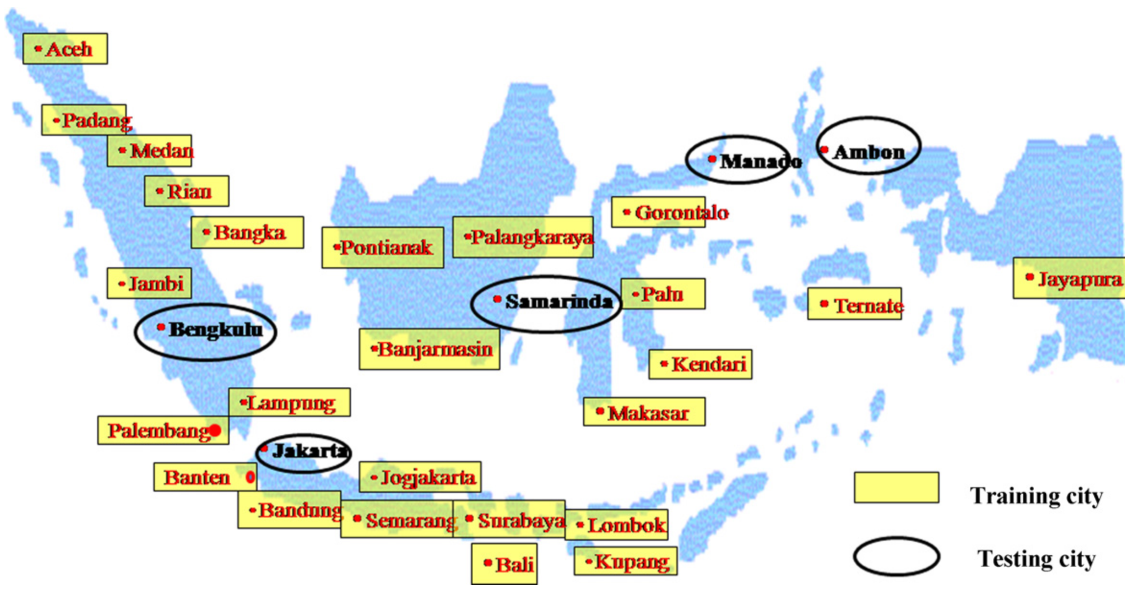

Fig. 1. The map of Indonesia and the selected training and testing city for ANN model.

6°N and 11°N latitudes and between 95°E and 141°E. The area of Indonesia consists of about 2,000,000 km^2 of land area and 3,000,000 km^2 of sea area. It is a huge archipelagic country extending 5120 km from east to west and 1760 km from north to south. Indonesia is the world's 16th-largest country in terms of land area. Indonesia has a tropical climate which varies from area to area. Commonly, the dry season occurs from June to September, while the rainy season occurs from December to March. The map of Indonesia is presented in Fig. 1.

Indonesia consists of five big islands (namely Sumatera, Kalimantan, Java, Sulawesi and Papua) surrounded by small islands which are facing energy problems. They face problems in energy demand because of island community characteristics, which are dependent on fossil fuel supplies from island to island that have high costs for transportation. Therefore, it is worthwhile to consider any possible self sustaining energy possibility. One such alternative energy source that can be utilized is solar energy available locally.

Utilization of a solar energy system requires knowledge about the solar irradiation potential in the different locations. In order to set up solar energy technology in the early stage, the knowledge about solar energy's potential is essential. Solar irradiation is used in the early stage for estimating the renewable energy potential. Solar irradiation potential is also required for crop models (in agriculture field) as well as for building thermal performance (in engineering field). In addition, a solar energy map is useful for further evaluating the renewable energy option and planning, such as for site location. For Indonesia, a solar energy map has not yet been compiled.

As developing country which has geographical condition such as island and widely remote area, the measurement of solar irradiation in the ground becomes difficult and expensive. There are large areas in the island of Indonesia that spread over from east to west that have no ground measurement. Estimation of solar irradiation data using appropriate model can be an alternative solution for a developing country, such as Indonesia. This paper studies about the development and usage of the ANN models for estimation of solar irradiation in such location.

In Indonesia, some meteorological stations only have relative humidity, temperature, wind speed, and sunshine duration recorders. Measurement of solar irradiation with reliable and calibrated pyranometers is not available or only available in a limited location. Based on a previous study by the authors [1], the application of photovoltaic in remote area in Indonesia is cheapest compared to gasoline generator electricity due to the high cost in transportation. Since the design of any cost effective solar energy system depends on reliable data, and measuring solar irradiation is costly, therefore a method to estimate solar irradiation should be explored.

Previous work by authors [2] suggested a model which could estimate the solar irradiation potential with ANN method by using meteorological data in many locations. However due to the limitation of meteorological data, it cannot cover the entire islands of Indonesia that has wide area from east to west. This study aims to use ANN model to estimate the solar irradiation potential for the entire country and develop the first solar map by provincial for monthly specific time.

In Indonesia, there are some difficulties in getting the situ data for the entire country due to the lack of measurement apparatus in the meteorological station, wide geographical condition, and the unavailability of database. To solve the problems that occur due to the lack of situ data, in this study we decide to use satellite data for modeling neural network is considered in order to estimate solar irradiation.

This study has two objectives to be considered. First, explore the ANN method for solar irradiation potential estimation in many locations in Indonesia based on satellite data. Second, introduce the GIS technology for solar energy mapping based on the result of ANN estimated value.

The contribution of this study is to develop neural network models for estimating monthly averages global solar irradiation potential in many locations of Indonesia based on satellite data. Solar mapping is developed based on predicting the value by ANN model proposed using GIS technology. The knowledge of solar resources availability at a particular geographical location is useful for solar engineers, building engineers, and agriculture engineers in many applications of solar energy. A solar irradiation map performs theoretical potential of solar energy for a specific region and provides information that useful for site selection of solar energy system. The theoretical potential can be an early stage for decision making to implement solar energy system.

So far, there is no solar irradiation map for islands of Indonesia. Without a database and information of most appropriate locations of renewable energy resources in the country, the decision makers and stakeholders of solar energy system facing difficulty for

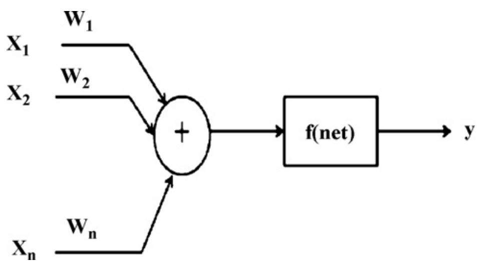

Fig. 2. A typical ANN model.

implementation. This can be achieved by developing solar irradiation map for the country. However, this study only limit to evaluate the resources potential, while other issues such as economic, and environmental were not considered. However, for further work, these aspects are considered to take into account.

This paper is organized as follows: literature review about ANN theory, GIS technology and previous works on estimating solar irradiation using ANN are described in Section 2. The database and the methodology that used in this study are presented in Section 3. The result and analysis are shown in Section 4. Finally, the conclusions are given in Section 5.

2. Literature review and previous works

This section describes about literature reviews and previous works on solar irradiation estimation by using ANN method and GIS.

2.1. Solar energy potential

Availability of solar energy on the ground surface is one of the consideration factors for implementation of solar energy system in the country area. Solar irradiation is defined as the amount of energy that reaches a unit area over a specified time, expressed as kWh/m^2. There are two components of solar irradiation, namely direct and diffuse irradiation. The sum of both components is known as global irradiation. In order to utilize the solar energy system, one of the influencing factors for its performance is the availability of solar energy on the ground surface that can be converted into heat or electricity. Therefore solar irradiation databases are important for successful planning, design, and operation of the solar energy system.

2.2. Artificial neural network (ANN) theory

Initially, an ANN can be divided into two parts, architecture and functional properties. The former defines the structure of the network as the number of artificial neurons and their interconnectivity. The latter includes the properties of the neurons and their connections, namely learning rate, initial weight and momentum. Learning rate term (L), indicates how much the weight change will effect on each pass. This is typically a number between 0 and 1. Momentum term (M), indicates how much a previous weight change should influence the current weight change. As the neuron passes values from one layer of the network to the next layer, the values are modified by a weight value in the link that represents connection strengths between the neuron. The weights of the connection between neurons are adjusted during the training process to achieve the desired input and output relation of the network. A typical ANN model is shown in Fig. 2.

The basic theory of ANN is reviewed based on this reference [3]. An artificial neuron has n inputs as x_i ($i = 1, 2, 3, \ldots, n$), which indicate the source of the input signal. Each input is weighted before reaching the main body of the artificial neuron by the connecting

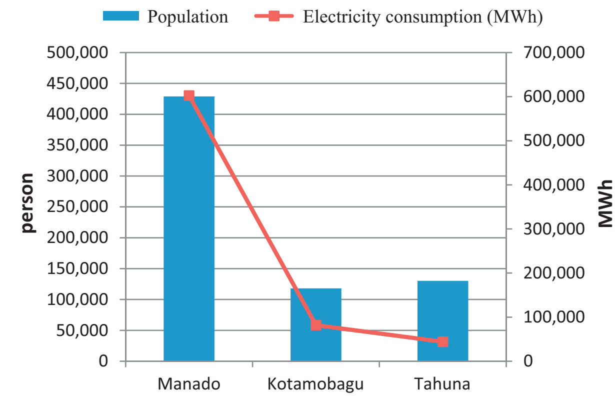

Fig. 3. The population and number of the electricity consumption (MWh) among the several cities in a province (the case of North Sulawesi province).

strength or the weight factor, w_j. Then, the signal passed through the connection strength is equal to a portion of the original signal, $w_j x_j$. On the other hand, for the neuron to produce a signal, the input signal to a neuron must exceed a threshold value, θ. By this way, the total signal net inside the neuron can be calculated with Eq. (1).

$$net = \sum_{i=1}^{n} x_i w_i - \theta = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n - \theta \rightarrow net$$
$$= W^T - \theta \tag{1}$$

After the effects of the threshold are applied on the weighted signal, the net is mapped with the use of an activation function f. The mapping should be linear or nonlinear according to the choice of the f function. The output y can be calculated by Eq. (2).

$$y = f(net) \tag{2}$$

This output may be an input for some other neurons. If there are many neurons in a network, then each neuron is called a node within the network. If there are m nodes in a network, then the above referred procedures will work for each one of them. In order to distinguish between each neuron, the subscript i will be used. Accordingly, inputs, weights, activation signals, output, threshold, and nonlinear function will all have an identification subscript.

The reason for including the nonlinearity function is to ensure the neuron's bounded response. This means that the actual response of the neuron is conditioned or damped as a result of large or small activating stimuli, and thus, it is controllable. Two of the most used nonlinearities are the hard limiter and the sigmoid. Most of the limiters have upper and lower limits as ± 1, or 0 and 1. In an actual ANN application, it is up to the user to choose the bounded values. However, the sigmoid is very popular because it is bounded, monotonic, has a simple derivative and is nonlinear. The hard limit is not monotonic, and it has a discontinuation at the origin, and hence, it is not easily differentiable, but it is linear with its upper and lower bounds.

One of the things that make ANN different from other approaches is their learning ability. The information gained by learning is stored as weights between the neurons. There are many learning algorithms for the ANN. However, the most known and used one is the back propagation. This algorithm provides a way to find the weights that can achieve the best mapping between the input and the output. Each weight is updated in each iteration by Eq. (3).

$$w_{jij}^{new} = w_{ji}^{old} - \eta \frac{\delta E}{\delta w_{ji}} \tag{3}$$

Table 1
City, Latitude and Longitude of data taken.

No.	City	Latitude	Longitude	No.	City	Latitude	Longitude
1	Aceh	03°40′N	98°38′E	16	Bali	03°50′S	122°30′E
2	Medan	04°15′N	97°30′E	17	Lombok	10°19′S	123°39′E
3	Padang	01°0′S	100°20′E	18	Kupang	05°30′S	104°30′E
4	Riau	0°30′S	102°45′E	19	Pontianak	03°0′S	104°50′E
5	Jambi	01°38′S	103°30′E	20	Palangkaraya	107°52′S	2°52′E
6	Palembang	7°17′S	112°45′E	21	Banjarmasin	7°49′S	110°22′E
7	Bengkulu	7°0′S	110°26′E	22	Samarinda	06°54′S	107°36′E
8	Lampung	08°20′S	115°00′E	23	Manado	08°45′S	116°30′E
9	Bangka	02°30′S	115°30′E	24	Palu	05°56′S	106°0′E
10	Banten	02°00′S	113°30′E	25	Makasar	02°28′S	140°38′E
11	Bandung	03°00′S	110°30′E	26	Kendari	06°09′S	106°49′E
12	Semarang	05°10′S	119°20′E	27	Gorontalo	01°30′N	116°30′E
13	Yogyakarta	0°54′S	119°51′E	28	Ambon	01°29′N	124°51′E
14	Surabaya	0°48′S	127°23′E	29	Ternate	03°43′S	128°12′E
15	Jakarta	0°35′N	123°05′E	30	Jayapura	03°50′S	102°12′E

Here, w_{ij} is the weight between the ith and jth neuron, η is the learning rate that shows the step amount on the error surface, and it assumes values between 0 and 1. E is the amount of the error which can be calculated by Eq. (4).

$$E = \sum_{k=1}^{L}\sum_{j=1}^{q}(b_{kj} - z_{kj})^2 \tag{4}$$

where b_{kj} is the observation and z_{kj} is the predicted value by the ANN.

The advantage of ANN compared to other conventional technique are listed as follows [4]:

- Neural networks can work with numerical or analogue data that would be difficult to deal with by other means because of the form of the data and because there are so many variables.
- The direct manner in which ANNs acquire information and knowledge about a given problem domain (learning interesting and possible non linear relationships) through the training phase.
- Neural network analysis can be conceived of as a “black box” approach in which the user does not require sophisticated mathematical knowledge.

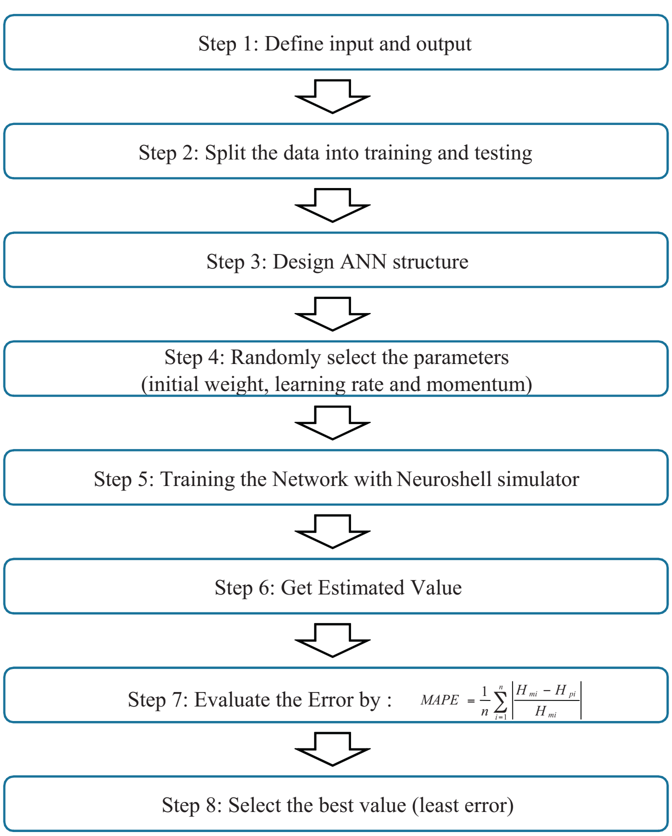

Fig. 4. The steps of ANN model which is used in this study.

2.3. Review about solar irradiation estimation based on ANN

There are several studies that predict monthly averages global solar irradiation potential based on the ANN method. Since ANN is highly nonlinear and requires no prior assumption concerning the data relationship, it has become a useful tool for predicting solar irradiation. Particularly, in the meteorological and solar energy resources fields, ANN based models have been successfully developed to model different solar radiation variable in many locations. Jiang [5] developed estimation of monthly mean of daily global solar irradiation using ANN method in China. The data period used are from 1995 to 2004 and the inputs for the networks are latitude, altitude, and mean sunshine duration.

Alawi and Hinai [6] developed ANN model in Oman for analyzing the relationship between the solar irradiation and climatologic variables in areas not covered by direct measurement instrumentation. Mohandez et al. [7] used the neural network approach for modeling monthly mean daily values of global solar radiation for locations in Saudi Arabia based on data: latitude, longitude, altitude and the sunshine duration as inputs. The result obtained MAPE for 10 locations used for testing, such as 10.7% for Tabuk station, 6.5% for Al-Ula station, 14.6% for Unayzah station, 10.5% for Shaqra station, 13.4% for Dawdami station, 10.1% for Yabrin station, 16.4% for Turabah station, 11.3% for Heifa station, 19.1% for Kwash station, and 13.5% for Najran station.

From the above reviewed, ANN models have been successfully demonstrated to have potential in estimating monthly average global solar irradiation by many researchers in many countries. However, these ANN models are location dependent and specific to each location. So far, there is no report about estimation of solar radiation potential for Indonesia by using the ANN method in many locations, except previous work by authors. In the previous work, Rumbayan and Nagasaka [8] have developed ANN to estimate solar radiation in Manado, a city in Indonesia. The input data to the network included monthly average temperature, monthly average relative humidity, monthly average wind speed, and monthly average sunshine duration. The result indicated that ANN model predicted with an accuracy of about 93% and a MAPE of 7.3% [8].

Table 2
Location for 30 cities and monthly solar radiation data (in KWh/m^2) as the input are given as polygon format in GIS environment.

City	January	February	March	April	May	June	July	August	September	October	November	December
Aceh	4.76	4.91	4.94	4.88	4.84	4.68	4.58	4.62	4.56	4.32	4.19	4.74
Medan	4.65	4.77	4.83	4.6	4.42	4.34	4.22	4.38	4.38	4.23	4.09	4.37
Padang	4.89	4.82	4.82	4.93	4.94	4.87	4.94	4.78	4.69	4.57	4.54	4.34
Riau	5.41	5.85	6.06	5.54	4.87	5.02	5.21	5.15	4.75	4.39	3.99	4.63
Jambi	4.85	4.86	4.88	4.69	4.69	4.61	4.71	4.88	4.85	4.59	4.18	4.64
Palembang	4.57	4.57	4.78	4.66	4.73	4.49	4.79	4.8	4.6	4.46	4.39	4.47
Bengkulu[a]	4.54	4.69	4.69	4.71	4.7	4.73	4.83	5.24	5.13	4.8	4.47	4.52
Lampung	4.64	4.77	4.94	4.85	4.92	4.87	5.06	5.12	5	4.67	4.48	4.43
Belitung	4.74	4.79	4.69	4.42	4.37	4.75	5.18	5.14	4.84	4.54	4.46	4.44
Jakarta[a]	4.57	4.65	4.85	4.95	4.96	5	5.07	5.21	5.42	5.4	4.84	4.74
Bandung	4.57	4.75	4.87	4.95	5.02	4.97	5.17	5.35	5.11	4.77	4.7	4.96
Semarang	4.85	5.04	5.14	5.15	5.21	5.59	6.1	6.64	6.21	5.05	4.9	5.15
Yogyakarta	4.37	4.72	4.8	4.65	4.52	4.56	4.93	5.4	5.61	5.13	4.98	4.52
Surabaya	4.64	4.84	4.9	4.81	4.64	4.71	5.24	5.81	5.83	5.03	4.85	4.79
Banten	4.74	4.96	4.94	4.77	4.88	4.98	5.43	5.77	5.52	4.88	4.8	4.95
Bali	5.21	5.5	5.64	5.14	5	5.29	5.84	6.11	6.1	5.55	5.29	4.9
Lombok	4.99	5.29	5.46	5.04	5.05	5.33	5.82	6.16	6.19	5.66	5.4	4.67
Kupang	5.56	5.96	6.37	5.78	5.96	5.88	6.7	7.16	7.54	7.41	6.68	4.6
Pontianak	5.17	5.17	5.11	5.08	5.03	4.98	5.31	5.3	5.2	4.99	4.85	5.27
Palangkaraya	4.97	4.92	4.86	4.81	4.8	4.77	5.01	4.96	4.95	4.7	4.64	5.01
Banjarmasin	5.04	5.05	5.03	4.92	4.84	4.88	5.29	5.51	5.27	4.66	4.75	4.77
Samarinda[a]	4.66	4.88	4.99	4.98	4.89	4.76	4.76	4.87	4.92	5.04	4.8	4.42
Manado[a]	5.61	5.77	6.04	6.24	6	5.65	5.87	6.53	6.61	6.19	5.69	5.59
Palu	5.24	5.34	5.43	5.28	5.46	5.2	5.7	5.84	5.6	5.22	4.98	5.67
Makasar	5.3	5.47	5.74	5.99	5.96	5.92	6.41	6.74	6.65	5.51	4.92	5.36
Kendari	4.64	4.8	4.66	4.63	4.44	4.27	4.69	6.05	6.3	5.46	4.8	5.61
Gorontalo	5.26	5.38	5.43	5.31	5.1	5.15	5.48	5.6	5.42	5.13	5	4.7
Ambon[a]	5.52	5.57	5.49	5.37	5.17	5.16	5.3	6	6.02	6.25	6.2	6.04
Ternate	5.73	6	6.08	5.73	5.36	5.4	6.04	6.32	6.23	6	5.75	5.14
Jayapura	4.95	5	4.97	4.9	4.8	4.76	4.89	4.99	5	4.93	4.87	4.57

[a] Cities selected for prediction, which their values of irradiation were predicted by ANN model.

2.4. Resources mapping using GIS

Geographic information system (GIS) is a system that captures, stores, analyzes, manages, and presents data that are linked to locations. In the simplest terms, GIS is the merging of cartography, statistical analysis, and database technology. GIS takes the number from databases and puts the information in the map as features. By mapping where and how things move over a period of time, the insight of profile can be gained.

The process of combining and transforming information from different layers is sometimes called map "algebra" insofar as it involves adding and subtracting information. If, for example, we wanted to consider the effects of widening a road, we could begin with the road layer, widen a road to its new width to produce a new map, and overlay this new map on layers representing land use. The ability to separate information in layers, and then combine it with other layers of information is the reason why GIS hold such great potential as research and decision-making tools [9].

This section reviews implementation of GIS technology to administrative solar energy resources. GIS models have been successfully used in performing solar radiation mapping in several countries. Sozen et al. predicted solar energy potential in Turkey using the ANN model and presented the monthly maps of solar energy [10]. Gastli and Charabi developed a solar radiation map in Oman using GIS [11]. In Europe and the USA, an entire solar radiation atlas has been developed by using GIS.

In GIS technology, not only solar energy potential but also other form of renewable energy potentials such as wind energy, hydro, biomass and geothermal energy can be developed. The study employs GIS to map the wind energy resources of Karnataka state in India has been reported by Ramachandra and Shruthi [12].

The renewable energy sources (RES) have some special "geographical qualities" for their treatment with GIS. So far, the solar radiation map over Indonesia has not developed yet. Based on the necessity, this work aims to study solar irradiation estimation in Indonesia with the ANN model and to present the estimated result as solar mapping over Indonesia using GIS technology.

3. Data and methodology

This research was conducted for Indonesia, which consist of 30 provinces. We selected the capital city of each province, which is the most populated and energy used are concentrated. For example, based on statistical data [13] in North Sulawesi, one of the provinces in Indonesia, the population and the electricity consumption are described as following Fig. 3.

In the Fig. 3, it can be observed that the capital city called "Manado city" is the most populated and therefore it has the most energy demand among the cities in North Sulawesi Province. This situation is similar applicable to the other 29 province in Indonesia, whereas the capital city is the biggest population concentrated as well as the highest energy demand.

In order to train the neural network, satellite data from 30 cities spread over Indonesia were used as training (25 cities) and testing (5 cities) data. The 30 cities selected

Table 3
The performance of MLP structures by statistical error.

MLP structure	Correlation (r) for training	MAPE (%) for testing
9-4-1	0.85	4.35
9-5-1	0.86	4.36
9-6-1	0.86	4.22
9-7-1	0.82	4.50
9-8-1	0.82	4.39
9-9-1	0.85	3.74
9-10-1	0.82	4.43
9-11-1	0.93	3.29
9-12-1	0.83	4.17
9-13-1	0.84	4.24
9-14-1	0.81	4.58
9-15-1	0.83	4.54

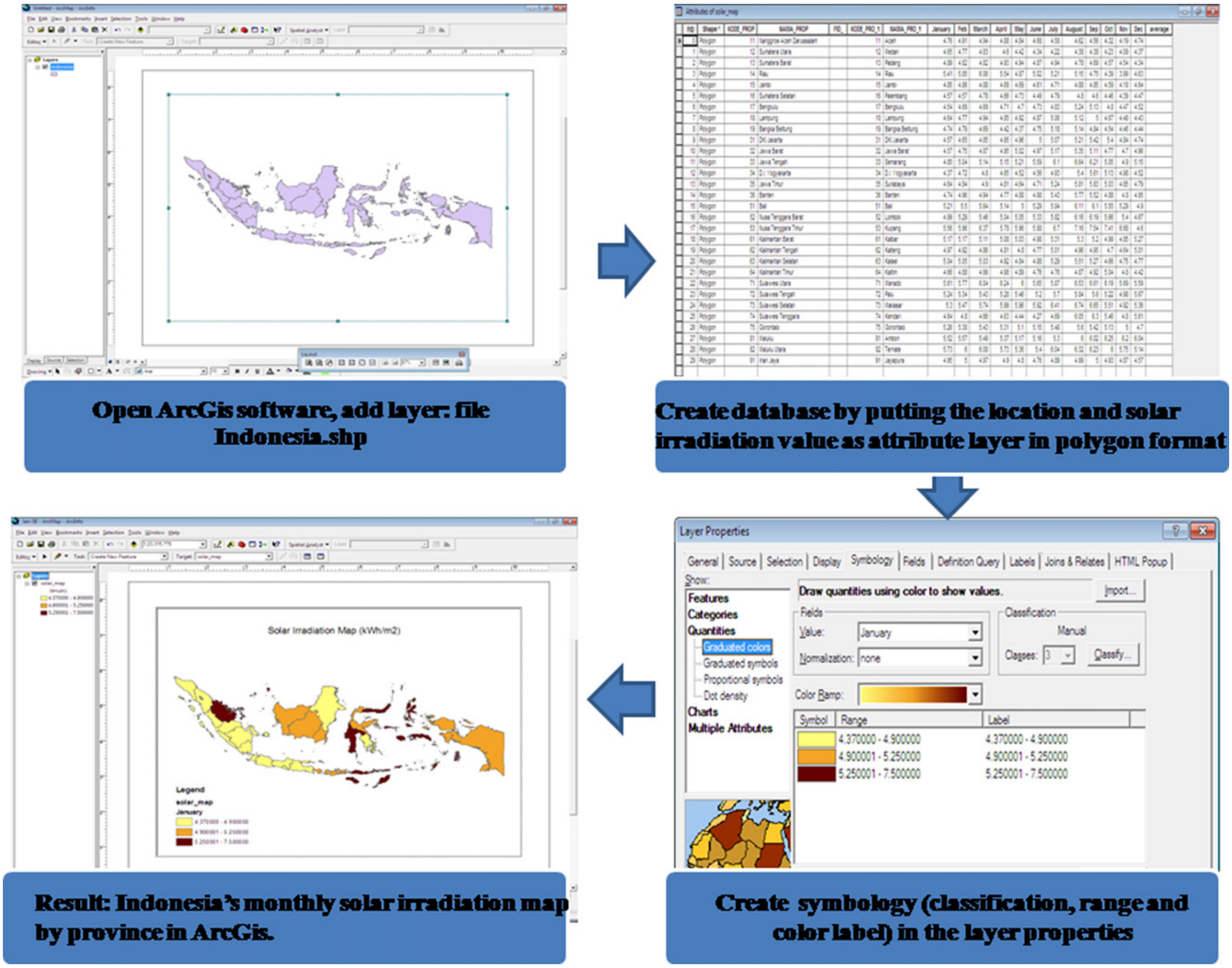

Fig. 5. The processes used in this study to generate Indonesia's solar irradiation map by province in GIS environment.

are the capital provincial (administrative region) in Indonesia. The data taken and the geographical condition in terms of latitude and longitude of these 30 cities are presented in Table 1.

The cities used for training and testing data are shown in Fig. 1. The 5 cities used for testing data i.e. Jakarta, Samarinda, Manado, Ambon and Bengkulu (They are indicated in the square on the map in the Fig. 1). These cities are representative of five big islands

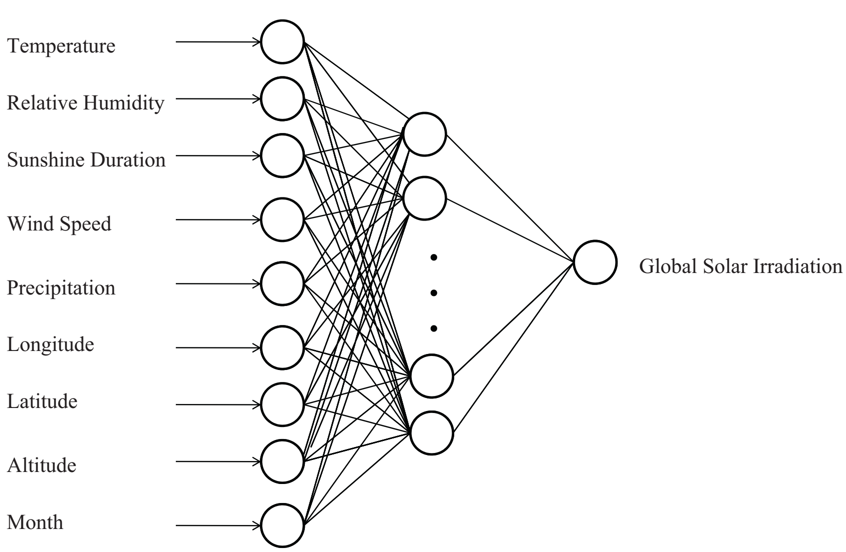

Fig. 6. The ANN model proposed for the best estimator proposed in this study.

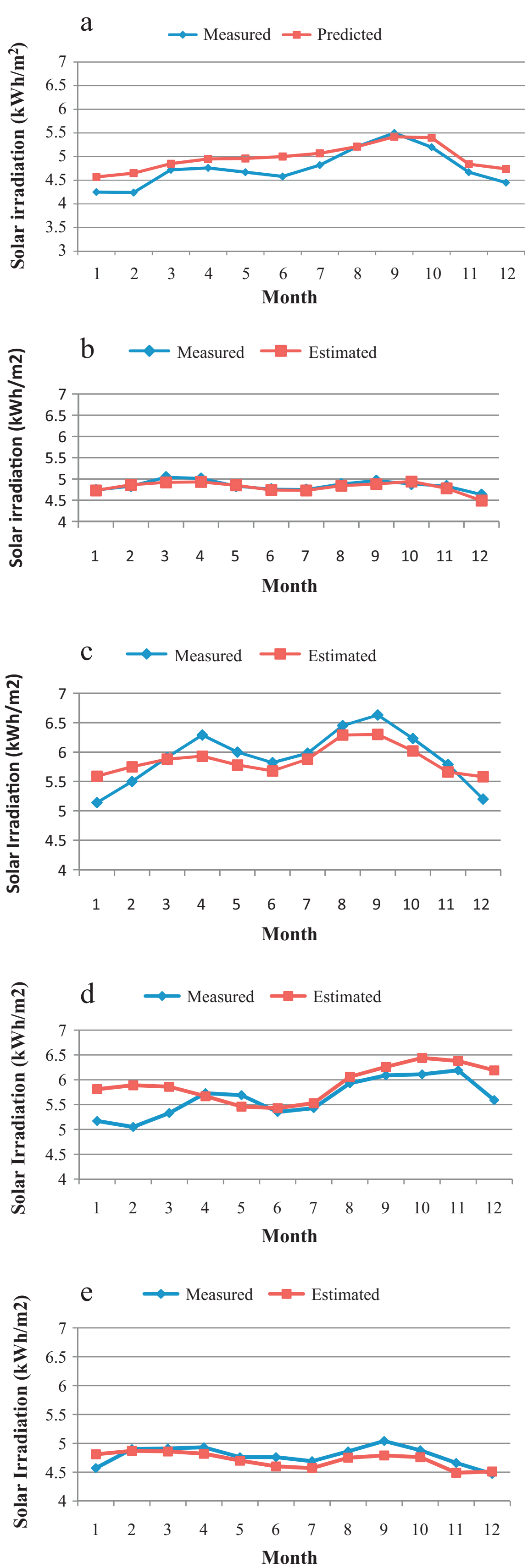

Fig. 7. (a) The comparison between measured and predicted values for Jakarta city. (b) The comparison between measured and predicted values for Samarinda city. (c) The comparison between measured and predicted values for Manado city. (d) The comparison between measured and predicted values for Ambon city. (e) The comparison between measured and predicted values for Bengkulu city.

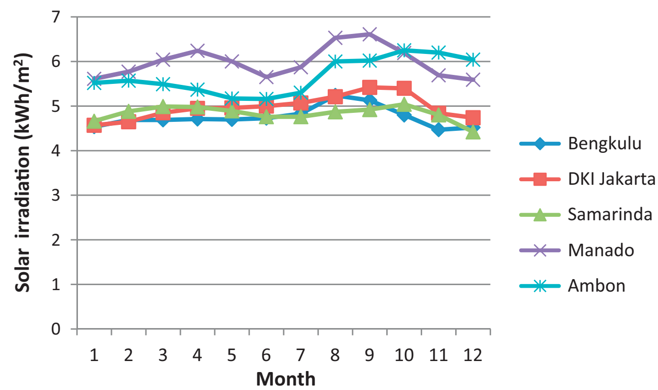

Fig. 8. The comparisons of predicted values of the monthly solar irradiation among the selected cities (Bengkulu, Jakarta, Samarinda, Manado, Ambon).

in Indonesia. Jakarta is located on the Java island, Samarinda is located on Kalimantan island, Manado is located on Sulawesi island, Bengkulu is located on Sumatera island, while Ambon is the city chosen that situated next to Papua island, which is representative of eastern part of Indonesia. The remaining cities indicated in the map were used for training data in the neural network proposed.

In order to guarantee the design model of ANN can work for the locations with have no data, the testing cities are not included in the training. The test cities are treated as unseen data in neural network. In the training section, the neural network is trained to find the relationship between input and output based on the algorithm as presented by Eqs. (1)–(4). Then the relationship will be applied for testing section to get the output by providing the input values.

In this study, ANN models were developed in order to define the solar resource potential in Indonesia. Several multi layer perception (MLP) structures were generated and tested. Back propagation algorithm was used to adjust the learning procedure. The steps that have been used in this study are presented in Fig. 4.

The procedure used in this study is described as follows: the first step to build the model is to define the data as the input and output in the neural network. Average temperature, average relative humidity, average sunshine duration, average wind speed, average precipitation, longitude, latitude, and month of the year were used as the input while monthly average solar irradiation was used in the output layer. Then the data were split into training and testing sections. Design of the development model of ANN by arranging the number of neurons in the hidden layer, or changing the parameter (initial weight, momentum, as well as learning rate) or network size. In this study, network size of ANN was defined as one input layer, one hidden layer and one output layer. The model was analyzed by using Neuroshell, which is a neural network simulator.

The predicted value will be occurred as result in training and testing data for each model ANN proposed and then evaluate how well the ANN model has been predicted the output. The comparison between measured and estimated value were evaluated by statistical error of mean average percentage error (MAPE) by Eq. (5).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{H_{mi}-H_{pi}}{H_{mi}}\right| \qquad (5)$$

where H_{mi} is measured values and H_{pi} is predicted values for monthly average global solar irradiation, n is the number of testing examples.

In MAPE, sign of errors are neglected and percentage errors are added up to obtain the average. MAPE is commonly used in quantitative forecasting methods because it produces a measure of relative overall fit. It usually expresses accuracy as a percentage.

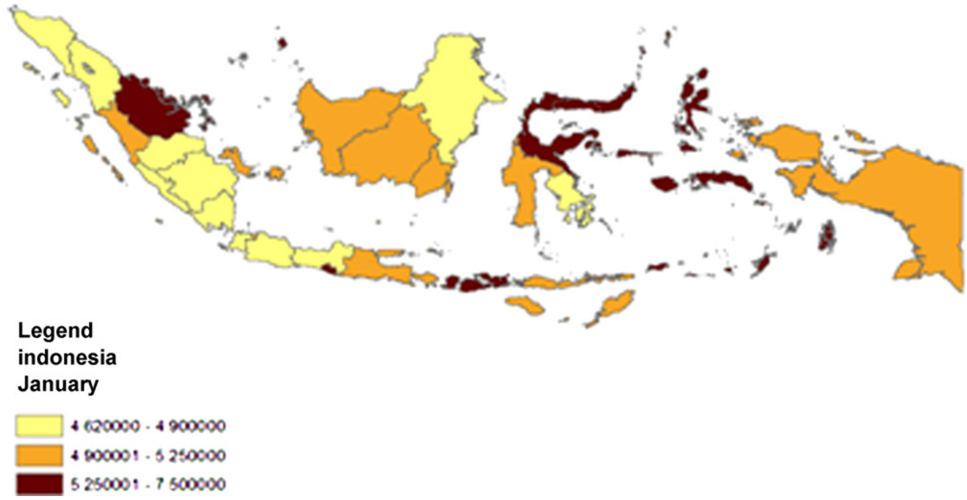

Fig. 9. Solar irradiation map by province in Indonesia on January.

Fig. 10. Solar irradiation map by province in Indonesia on February.

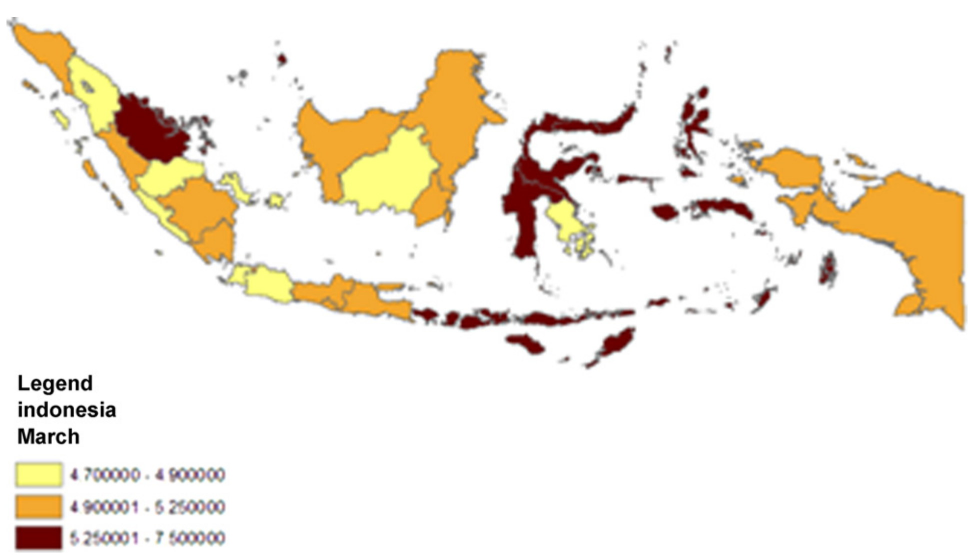

Fig. 11. Solar irradiation map by province in Indonesia on March.

Fig. 12. Solar irradiation map by province in Indonesia on April.

Fig. 13. Solar irradiation map by province in Indonesia on May.

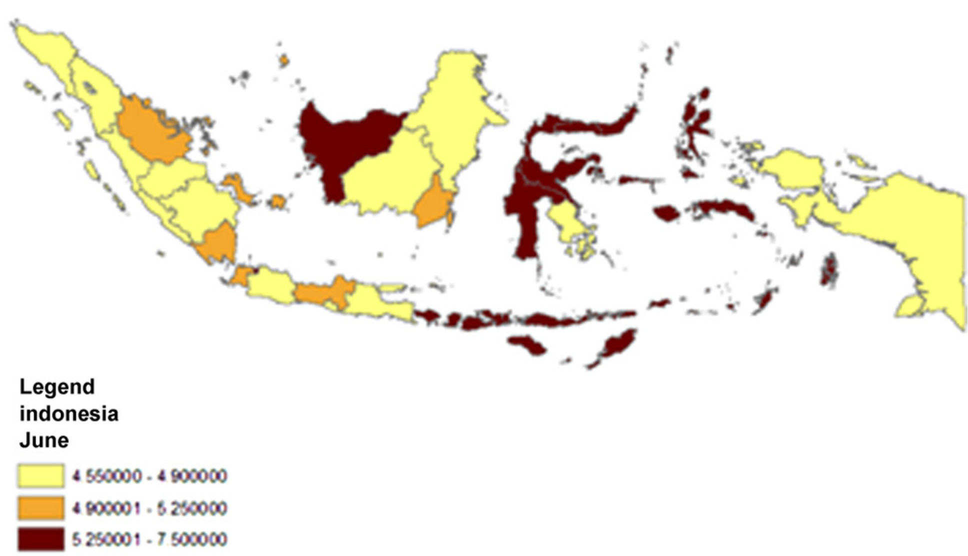

Fig. 14. Solar irradiation map by province in Indonesia on June.

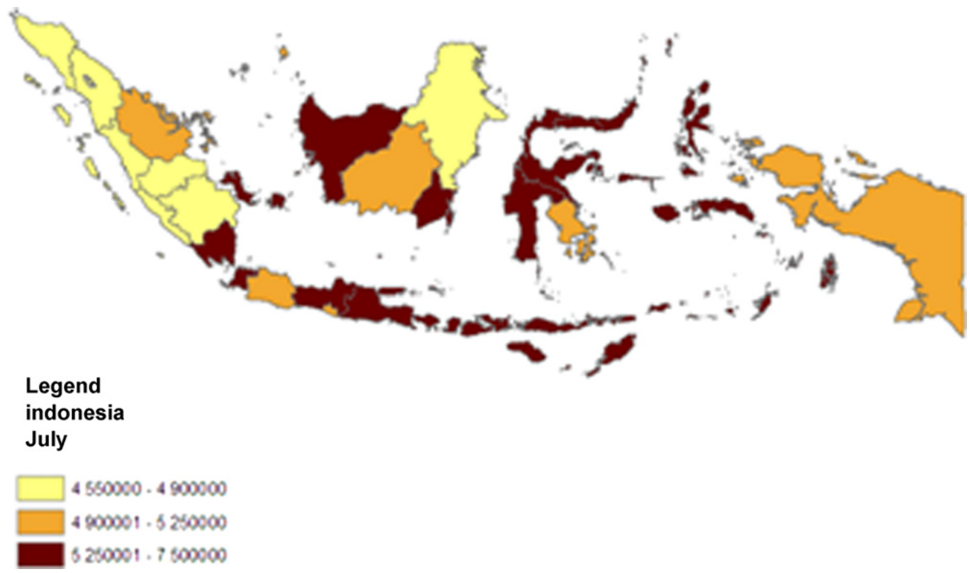

Fig. 15. Solar irradiation map by province in Indonesia on July.

The lowest MAPE indicates that the proposed network achieved the acceptable result.

The final step is to apply the result of the best proposed model with estimated value by ANN (for 5 testing cities) and solar radiation data value (for 25 training cities) for mapping solar energy in the GIS environment. As GIS can visualize, question, analyze, interpret, and understand data in many ways that reveal relationships, patterns, and trends in the form of maps, globes, reports, and charts.

In this study, ArcGIS was used as effective tool to visualize the map of solar resources by provincial boundaries in monthly basis. ArcGIS was developed by Environmental System Research Institute (ESRI). The data that used are 30 cities locations and their solar irradiation value given as polygon format in GIS. We used data collection from the monthly average solar irradiation, which consists of 22 years period from NASA website (http://eosweb.larc.nasa.gov). The monthly solar irradiation data that put in GIS environment were presented in the Table 2. The GIS processes that used to generate solar map by province in this study are presented in Fig. 5.

By using GIS as a toll to visualize the solar irradiation data, we can obtain the final solar map in the monthly basis which shows the potential of solar irradiation in the entire of Indonesia.

4. Results and analysis

4.1. Solar irradiation estimation using ANN in Indonesia

In this work, a model built by training ANN is employed in order to estimate the output. Then the neural networks have been shown to be able to recognize patterns (in the training data) and to generate accurate input–output relationships. They have been applied towards predicting the output in the testing data. By setting up the parameter of network training as 0.3, 0.1, and 0.3 for learning rate, momentum, and weight, respectively.

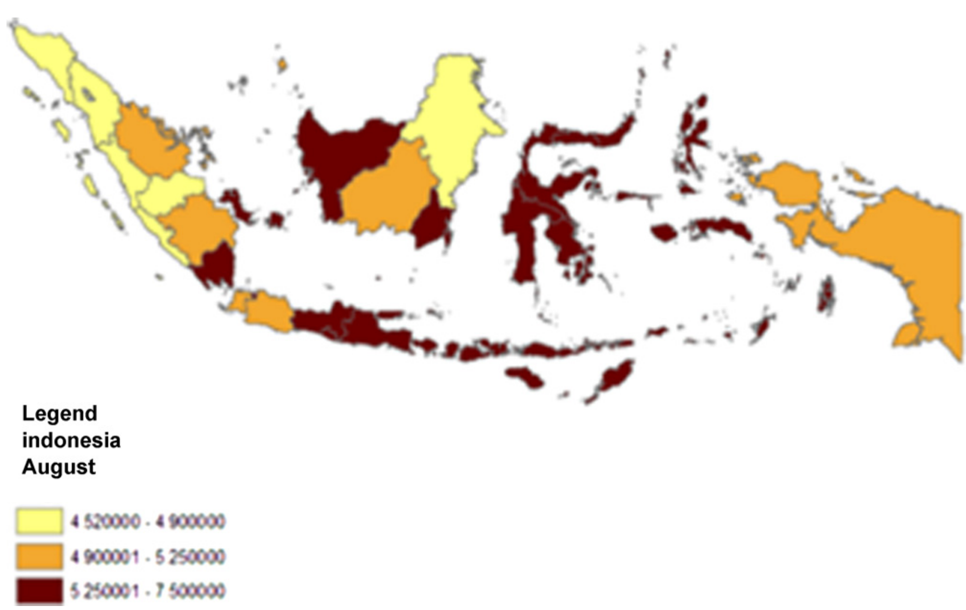

Fig. 16. Solar irradiation map by province in Indonesia on August.

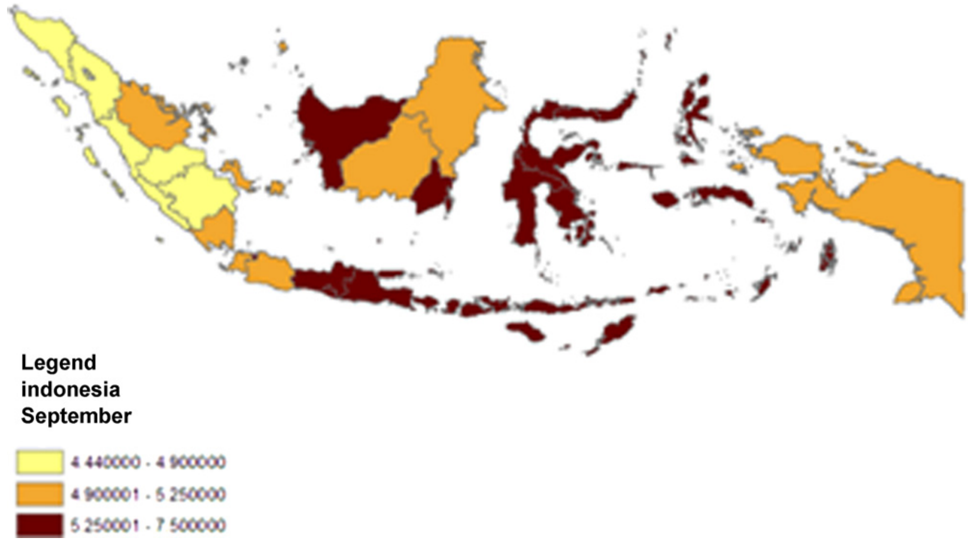

Fig. 17. Solar irradiation map by province in Indonesia on September.

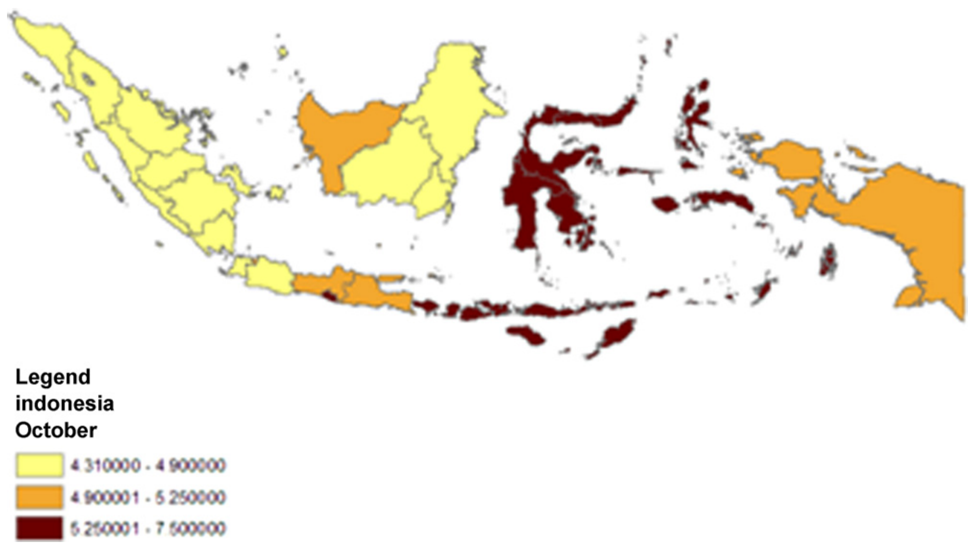

Fig. 18. Solar irradiation map by province in Indonesia on October.

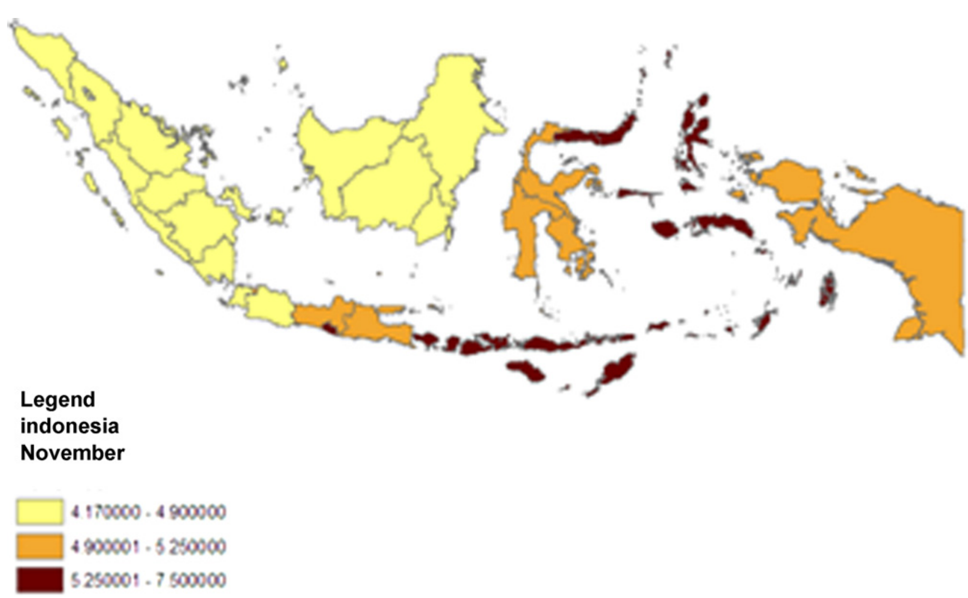

Fig. 19. Solar irradiation map by province in Indonesia on November.

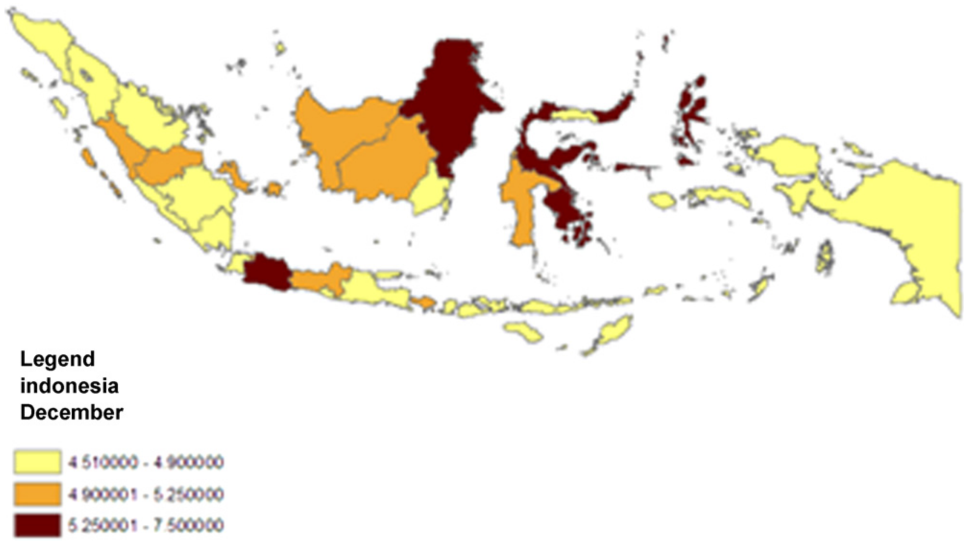

Fig. 20. Solar irradiation map by province in Indonesia on December.

The feed-forward back propagation algorithm with single hidden layer was used in this analysis. The ANN models were developed by varying the number of neurons in hidden layer. Several attempts of MLP structures have been developed and trained in the Neuroshell software. The MLP structures indicate the number of neurons in the input layer, hidden layer and output layer. The comparisons of measured and estimated values are examined by statistical error (MAPE) by Eq. (5). The performances of different MLP structures (input–hidden–output neurons) proposed in this study were given in Table 3.

As shown in Table 3, the result of all ANN models has achieved significant agreement between the estimated and measured values of monthly average global of solar irradiation at below 5% of error. The least MAPE of 3.29% can be achieved by the best estimator with MLP structure that consists of 9, 11, 1 neurons in the input, hidden, and output layers, respectively. The best estimator model proposed of ANN was selected and presented in Fig. 6.

Measured and estimated values of solar irradiation for five cities of testing were presented in Fig. 7a–e. The result gives significant correlation between measured and estimated values for evaluating the solar energy potential at the unknown locations as treated in the testing network.

It is found that MAPE for 5 locations used for testing, such as 4.9% for Jakarta (Fig. 7a), 1.2% for Samarinda (Fig. 7b), 2.7% for Manado (Fig. 7c), 4.5% for Ambon (Fig. 7d) and 3.5% for Bengkulu (Fig. 7e), respectively. It indicates the significant agreement between measured and predicted values has achieved. The performance of ANN models proposed in this study proves that it work well in order to estimate solar irradiation potential over Indonesia.

The comparisons of predicted values of the monthly solar irradiation among the selected cities (Bengkulu, Jakarta, Samarinda, Manado, Ambon) are presented in the following Fig. 8.

The results show that the monthly average solar irradiation is varying from each city. For Bengkulu, the value of predicted solar irradiation is highest in August and the lowest value in November. The yearly average of solar irradiation value was found to be 4.75 kWh/m^2. For Jakarta, the value of predicted solar irradiation is highest in September and the lowest value in January. The yearly average of solar irradiation value was found to be 4.97 kWh/m^2. For Samarinda, the value of predicted solar irradiation is highest in December and the lowest value in October. The yearly average of solar irradiation value was found to be 4.83 kWh/m^2. For Manado, the value of predicted solar irradiation is highest in August and the lowest value in December. The yearly average of solar irradiation value was found to be 5.98 kWh/m^2. For Ambon, the value of predicted solar irradiation is highest in October and the lowest value in June. The yearly average of solar irradiation value was found to be 5.67 kWh/m^2.

The result shows that in average, solar irradiation value for Manado is the highest solar irradiation value followed by Ambon then Jakarta, Samarinda and Bengkulu. Manado and Ambon are located in eastern part of Indonesia, while the rest cities are located in the western part of Indonesia. As the limitation of ground measurement of solar irradiation, the model of ANN can be an option in order to estimate the potential of solar irradiation in many areas of Indonesia. This study successfully confirms the ANN model for the case study of Indonesia. By knowing average temperature, average relative humidity, average sunshine duration, average wind speed, average precipitation, longitude, latitude, and month of the year were used as the input in order to estimate solar irradiation output. The solar irradiation profile in Indonesia can be important information for decision maker and engineer to explore the resource of solar irradiation for solar energy system.

4.2. Solar irradiation mapping

The estimated solar potential values from the ANN were presented in the form of monthly maps to derive spatial database. The solar irradiation values were divided in three classification, i.e. low (below 4.9 kWh/m^2), medium (4.9–5.25 kWh/m^2) and high (above 5.25 kWh/m^2). This study is carried out in the scale of 1: 50,000,000. Digital maps of provincial boundaries with typical monthly solar energy availability were presented in Figs. 9–20.

The darkest color in the map indicates that the most solar energy potential in that location. The priority map can be used as an early stage for decision making to capture the solar energy as sustainable development. This can be used as basic study to identify the potential for solar radiation over Indonesia. The map indicates variations across the locations of the study area over Indonesia.

It is clear from Figs. 9–20 that seasonally, the majority of land in Indonesia receives high potential of global solar irradiation. The value of solar irradiation over Indonesia ranging between 4.6 kWh/m^2 and 7.2 kWh/m^2. It is found that there is no location plot in the low class.

The solar map identifies the most and least suitable potential areas of energy in terms of radiation availability. This map is

useful to administrate the global energy resources on the islands of Indonesia, especially for the location that lack ground measurement. This can be a tool for further analysis to implement the solar energy system in Indonesia.

The profile about solar irradiation availability in terms of theoretical potential has been presented. As seen in the solar map, the availability of the solar irradiation profile can be referred to priority sites for renewable energy development. The eastern parts of Indonesia have the most solar-energy potential for solar energy systems during the whole year, especially in Bali, Lombok, Kupang, Manado, Palu, Makasar, Gorontalo, Ambon, and Ternate. This shows that Indonesia has high potential for solar energy. Spatially, the eastern parts of Indonesia's islands receive more solar irradiation than the western part.

By mapping solar irradiation in the average monthly period of the year, decision maker and engineer can gain insight from the profile and study the path of theoretical potential of solar irradiation availability. However, in the course of exploitation, constraints such as land use, geographical area and economic condition will be encountered. In addition, several solar energy technologies are limited by different factors. Therefore it is necessary for further research to examine the technical and economic potential of solar energy from the viewpoint of a specific location and technology system.

5. Conclusion

This paper presents a study on theoretical solar irradiation potential using ANN and GIS technology. The result indicates that the ANN model developed here can be utilized for estimating the solar irradiation potential over Indonesia. The solar mapping of 30 provinces of Indonesia are presented in the monthly map by using GIS technology with ANN predicted values.

This study proves that ANN can be used for estimating global solar irradiation potential in some locations in Indonesia. The ANN model successfully estimates unknown locations using tested cities such as Jakarta, Samarinda, Manado, Ambon and Bengkulu as 4.9%, 1.2%, 2.7%, 4.5% and 3.5% respectively. As test cities are treat as unseen data in the neural network, it indicates that the model can be applied to location that does not exist data. The ANN method can be useful in remote locations for island sites in Indonesia which lack ground measurement.

In addition, spatial mapping for theoretical solar energy potential has been developed. The model establishes a method in which to create a spatial picture of the potential of solar energy resources over Indonesia for the provincial administrations.

These maps can provide useful information for national as well as regional and local renewable energy planning in the islands of Indonesia. They are the first maps to be published in the literature and will benefit decision makers and engineers to develop solar energy systems. Proposed method based on data available can be an early stage to provide solar map by province for the entire of Indonesia. We have done GIS with reasonable result to generate solar map by province for the country case by using data available in this proposed method, however if one wants to calculate spatial analysis by point, then we need to consider another method such as Inverse Distant Weight or Kriging in GIS environment. However, it needs a huge number of data that unfortunately is not available for this research at this moment. In the future, if these data available, spatial analysis for mapping solar energy should be considered.

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